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Review

Demand Response in Buildings: A Comprehensive Overview of Current Trends, Approaches, and Strategies

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Abstract: Power grids in the 21st century face unprecedented challenges, including the urgent need to combat pollution, mitigate climate change, manage dwindling fossil fuel reserves, integrate renewable energy sources, and meet greater energy demand due to higher living standards. These challenges create heightened uncertainty, driven by the intermittent nature of renewables and surges in energy consumption, necessitating adaptable demand response (DR) strategies. This study addresses this urgent situation based on a statistical analysis of recent scientific research papers. It evaluates the current trends and DR practices in buildings, recognizing their pivotal role in achieving energy supply–demand equilibrium. The study analysis provides insight into building types, sample sizes, DR modeling approaches, and management strategies. The paper reveals specific research gaps, particularly the need for more detailed investigations encompassing building types and leveraging larger datasets. It underscores the potential benefits of adopting a multifaceted approach by combining multiple DR management strategies to optimize demand-side management. The findings presented in this paper can provide information to and guide future studies, policymaking, and decision-making processes to assess the practical potential of demand response in buildings and ultimately contribute to more resilient and sustainable energy systems.

Keywords: smart grid; smart buildings; demand response; demand response modeling; demand response management strategies

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1. Introduction

Some challenges the 21st century faces include pollution, climate change, and the depletion of fossil fuel reserves. Consequently, suitable alternatives to fossil fuels should be identified to mitigate further climate change and pollution. Renewable energy sources are widely regarded as environmentally friendly. However, as the penetration of renewable energy increases, electricity production shows greater uncertainty and variability due to the intermittent nature of resources like solar and wind power [1]. Additionally, modern power grids face other challenges, such as extreme weather conditions resulting from climate change and growing global energy consumption, as living standards improve [2,3]. The difference between peak and low demand leads to higher network losses and shorter equipment life [4]. To address these supply and demand challenges, future energy networks will have to rely on storage, reserves, and demand-side resources. Among these solutions, demand response (DR) is recognized as a key approach that provides flexibility in energy usage [5,6]. Specifically, DR alters energy consumption patterns in response to price changes or incentive programs aimed at reducing usage during periods of high market prices or system reliability concerns [7]. In essence, DR focuses on adjusting the load flexibility [8]. Figure 1 presents a comprehensive schematic of the current challenges in power grid management, the underlying circumstances that lead to these challenges, and the proposed solution for future power grids.

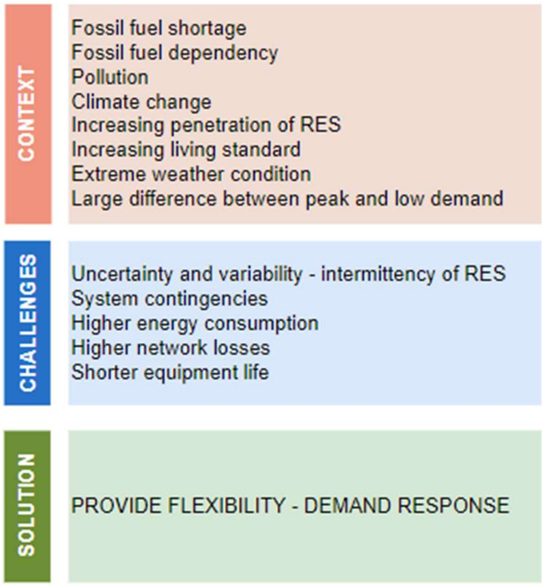


Figure 1. Circumstances and challenges of modern power networks, including an appropriate solution.

Given that buildings in the EU account for 43% of the final consumption [9], they have a role in solving the imbalance between supply and demand in energy networks. The energy flexibility of buildings is the possibility of altering energy consumption and the energy production of buildings [1] while also considering the preferences of the end users [10]. The solution incorporates all flexible building resources: the building system (HVAC, installed equipment, electric vehicles), the building itself (envelope), and occupant behavior toward energy [11]. Additionally, the flexible resources of a building can be categorized as demand-side and supply-side, where the demand-side includes thermostatic loads (e.g., HVAC) and non-thermostatic loads (e.g., appliances, lighting), while supply-side flexibility includes the power grid, renewable energy, energy storage, and the ability to dissipate energy from storage systems [12].

The increasing number of recent scientific papers on the subject at hand confirms the importance of demand response (DR) in buildings as an effective strategy to tackle the mentioned issues. A search conducted on ScienceDirect, a comprehensive scientific database, reveals a noteworthy rise in research papers and literature reviews focusing on the subject of "demand response in buildings" during the last decade, as shown in Figure 2 [13]. In the past ten years, there has been a significant increase in the number of research papers on this subject, experiencing a growth of over fivefold. Similarly, the number of literature review papers has seen an impressive increase of nearly sevenfold during the same period. The increase signifies a substantial growth of scholarly interest and research in this area.

Most research on the energy flexibility of grid-interactive buildings focuses on the hybrid application of energy sources and the optimal DR strategy for energy supply and demand [2]. It should be noted that previous research mostly quantifies the energy flexibility for only one type of building [14]. For example, in a simulated medium-sized commercial building located in Virginia, USA, ice storage was combined with DR and PV, and the results show that this combination gives a peak load reduction of about 89.50% [15]. In ref. [16], adjusting room heat consumption in response to wholesale electricity prices was proposed for a multi-room house in Denmark, where an economic model predictive controller (EMPC) was designed, and the results show that EMPC reduced the cost of electricity consumption by up to 37% per week. There are also numerous other studies, such as the impact of different control schemes on the energy flexibility of residential buildings in Canada [17], the development of an intelligent model for planning the operation of plug-in hybrid electric vehicles, washing machines, and dishwashers in residential buildings [18], and the establishment of a systematic approach to quantifying building electricity flexibility in office buildings, where the flexibility factors include building thermal mass, lights, heating, ventilation, air conditioning systems, and occupant behavior [19]. A few papers rely on a large-scale building model for estimating DR. Costanzo et al. [20] developed a distributed MPC scheme with an RC building model and applied it to 100 buildings. Ma et al. [21] proposed an energy management framework to achieve optimal operation of smart building clusters and described the processes of information exchange between smart building cluster operators and participating smart buildings. Gils [8] performed the first assessment of the theoretical DR potential for all consumer sectors in Europe. The Lawrence Berkley National Laboratory conducted a comprehensive study of California's demand response potential in three parts: Part 1 [22], Part 2 [23], and Part 3 [24]. The study includes advanced metering, demographic data analysis, and technology to address the challenges to meet the changing needs and future capacity of California's electric grid.

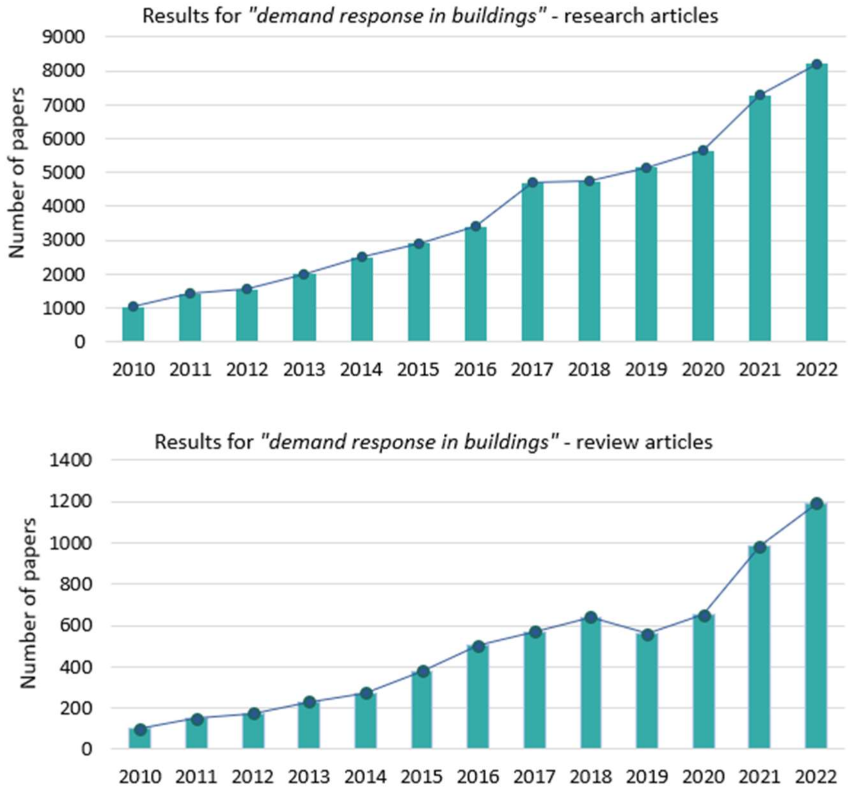


Figure 2. The total number of published papers on the subject of DR in buildings over the years [13].

Previous review papers have employed a wide range of building models to analyze the potential of demand response (DR) in buildings and have considered various management strategies or focused solely on specific strategies or technologies. A notable review paper is Ref. [2], which synthesized state-of-the-art research on energy demand flexibility. These reviews encompassed various measures ranging from renewable energy sources to HVAC, energy storage, building thermal mass, appliances, and customer behavior. Furthermore, Ref. [1] shed light on the potential of buildings to provide demand flexibility, outlining the challenges involved in harnessing this potential. Additionally, Ref. [25] systematically reviewed methods and applications for quantifying the energy flexibility of residential buildings. This comprehensive review categorized flexibility applications across building, district, system, and sector levels, outlining peak power reductions of 1% to 65% and energy savings of up to 60%. Studies often provide an overview of demand response strategies and approaches to using specific technologies. For example, studies like [26] concentrated on the utilization of pre-cooling and solar pre-cooling as a demand response strategy in buildings, providing detailed steps for designing and implementing these technologies. Similarly, Ref. [27] reviewed data-driven smart building-integrated photovoltaic (SBIPV) systems, emphasizing the challenges and objectives of utilizing data to optimize the performance of SBIPV systems. These focused reviews significantly expanded the relevant knowledge base by delving into specific technologies and strategies.

Though these studies have enriched an understanding of various aspects of demand response in buildings, this paper provides details on solutions to DR building modeling and DR management strategies and identifies correlations between the analyzed building models and strategies based on the size of the building sample in a particular study. Ensuring a relevant and up-to-date analysis requires incorporating the latest research findings in this overview, and we offer a contemporary perspective on the subject. The insights from this overview are valuable recommendations for future research endeavors and the development of energy flexibility in buildings. Such advancements are crucial for ensuring the reliability and resilience of power grids.

This paper follows a specific structure. Section 2 describes the fundamental terms related to DR, including approaches to DR modeling and DR management strategies. The section establishes a solid foundation for understanding the subsequent analysis. Section 3 conducts a correlation analysis by statistically examining the analyzed research papers. It seeks to establish correlations between the characteristics of the buildings studied, on the one hand, and adopted DR modeling and management strategies on the other. Section 4 presents the findings and a comprehensive discussion of the results obtained from the correlation analysis. The significant trends, observations, and implications are highlighted, providing a deeper understanding of the effectiveness of various DR approaches and strategies for different types of buildings. Furthermore, Section 4 provides a brief conclusion summarizing the key findings and contributions of the paper.

2. Fundamental Concepts Related to Demand Response (Dr)

2.1. DR Modeling Approaches

Different modeling approaches are used to estimate the potential of DR in buildings and assess the capacity of buildings to adapt energy consumption patterns in response to changing grid conditions [28]. DR modeling approaches can be broadly categorized into three main types: (1) white box (physics-based), (2) black box (data-driven), and (3) gray box (combination of physics-based and data-driven) [29].

As the initial approach, the white-box method views building energy models in terms of heat and mass equations [30]. This approach, often implemented in commercial software, such as *TRNSYS* [31], *EnergyPlus* [32], and *Modelica* [33], provides highly accurate energy consumption models [34]. However, the white-box model often fails to accurately capture the impact of household heterogeneity, occupant behavior, and usage patterns [11]. Additionally, it relies on abundant data, which can be challenging to obtain or not readily available. Furthermore, the white-box model typically demands substantial resources for modeling and simulation time, making it more suitable for individual building models rather than neighborhood or city simulations.

On the other hand, the black-box model does not require specific physical information but relies on calibrated functions and a specific dataset that describes the dynamic behavior of a building [35]. Techniques such as multiple linear regression (MLR), genetic algorithms (GA), artificial neural networks (ANN), and support vector machines (SVM) are commonly used to establish black-box models [36]. Employing a black-box model allows quantifying the flexibility of a building's demand directly based on credible measured data and occupant behavior, which otherwise is not captured by the white-box model. However, the black-box model requires a lot of high-quality data and often lacks interpretability [37,38].

A hybrid model known as the gray-box model bridges the advantages of both approaches. The gray-box model incorporates components modeled using the white-box approach, while other components are empirically fitted using measured data, essentially employing a black-box model [39]. The gray-box and black-box models are well-suited to assessing flexibility at aggregated levels, whereas the white-box model is best for individual flexible load assessments and optimization schedules [11].

In summary, the white-box model prioritizes a comprehensive understanding and explicit depiction of the system; the gray-box model blends partial knowledge regarding the building characteristics with data-driven methods; and the black-box model relies solely on data to model intricate relationships. Selecting a type of model depends on the existing knowledge of the building characteristics, the desired interpretability level, and the specific needs of the modeling task. The following table (Table 1) compares the above-mentioned approaches to modeling demand response (DR). It highlights an understanding of building physics and technical systems, dependence on data, interpretability and explainability, as well as computational requirements.

Table 1. Comparison of white-box, gray-box and black-box models.

Model Type	White Box	Gray Box	Black Box
Knowledge of building physics and technical systems	Detailed understanding and explicit representation of the whole system	Limited knowledge combined with data-driven techniques	No knowledge, purely data-driven
Data dependency	Moderate	Moderate	High
Interpretability and explanability	High	Moderate	Low
Computational requirements	High	Moderate	Low to moderate

2.2. DR Management Strategies

DR management strategies play a crucial role in the energy flexibility of buildings, enabling building owners and occupants to optimize energy consumption while also contributing to grid stability. These strategies can be categorized into five types: efficiency, load shedding, load shifting, modulation, and generation [40]. Extensively studied and implemented in diverse circumstances, these strategies have demonstrated and promoted efficient energy use and addressed the evolving requirements of buildings.

Efficiency means achieving a sustained reduction of energy consumption regardless of the time of day while reflecting a long-term commitment to such outcomes [25]. For example, enhancing the insulation and sealing of a building envelope leads to significant improvements in energy efficiency, reducing the need for heating and cooling, resulting in long-lasting energy savings.

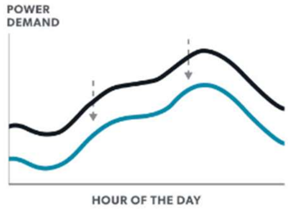
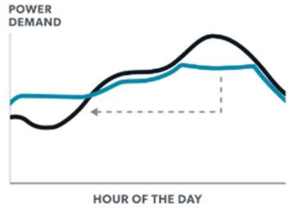
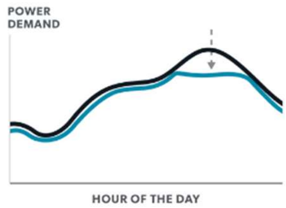
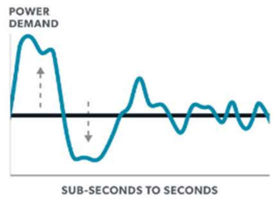
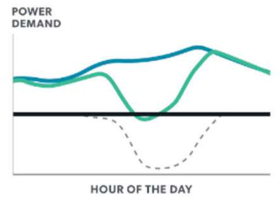
Load shedding reduces power consumption temporarily to meet peak capacity demands and supports the system during emergencies or contingency situations [1]. Examples of load-shedding technologies include interruptible processes, advanced lighting controls, and air-conditioning cycles [23].

Load shifting refers to flexibility in shifting building loads from peak to off-peak hours, typically using dispatchable resources [3]. This can be achieved, for example, by rescheduling high-load household appliances to off-hours [36] or adjusting the charging schedule of electric vehicles [41].

Modulation is the dynamic adjustment of demand in response to received grid signals, necessitating frequent adjustments in time intervals of seconds or even subseconds [25]. For instance, in an advanced smart grid system, household appliances equipped with real-time communication capabilities modulate energy consumption in response to instantaneous price signals received from the grid while optimizing usage patterns for maximum efficiency. Though the magnitude of demand changes is relatively small, participants in this type of demand response should be capable of swiftly modulating loads on short timescales [42].

Generation, as a demand response service, is the on-site production of electricity for local consumption or to be dispatched to the grid during periods of peak demand [25]. Table 2 gives a comprehensive overview of each strategy, showcasing the main characteristics, key figures on effectiveness, timeframe for demand reduction, and a graphical presentation of the load profile for each strategy.

Table 2. Comparison of DR strategies for efficiency, load shift, load shed, load modulation, and energy generation.

DR Strategies in Building	Characteristics	Key Features	Timeframe for Demand Reduction	Load Profile [43]
Efficiency	Improve energy efficiency through building upgrades and retrofits	Reduced energy consumption, lower carbon emissions, potential cost savings	Continuous and long-term impact	
Load shift	Shift non-essential energy consumption activities to off-peak hours	Change in energy usage patterns, potential cost savings during off-peak periods, grid support	Immediate impact during shifted hours	
Load shed	Temporarily reduce or interrupt non-critical energy loads during peak demand	Reduction in peak load demand, grid stability support	Immediate impact during peak demand periods	
Load modulation	Dynamically adjust energy consumption of specific building systems or equipment.	Flexibility in response to grid signals, optimized energy usage, grid support	Real-time or near-real-time response to grid signals	
Energy generation	Deploy on-site power generation sources	Localized energy generation, reduced reliance on the grid, grid support	Ongoing impact based on generation capacity and demand	

3. Literature Review

This analysis used a meticulously chosen sample of the most recently published scientific research papers [44–93] that were published over the past three years. Figure 3 visually depicts the geographical distribution and the publication year of the scientific papers. It clearly shows that the selected sample covers research from different continents and climates around the globe.

Of the total of six research papers [45,46,50,51,57,66], the geographical location of the analyzed buildings was not specified; however, in three research papers [52,53,63], the geographical location is specified only in terms of climate zones, indicating a broader coverage of geographical areas.

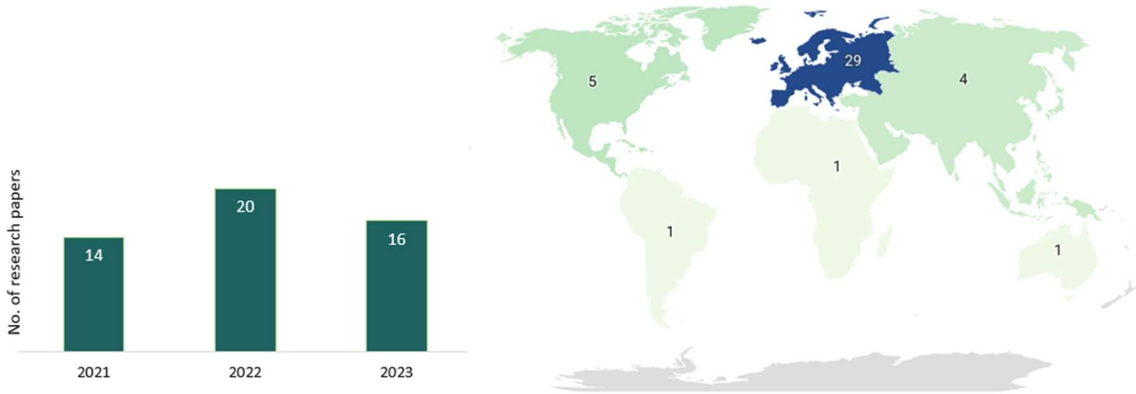


Figure 3. Analyzed research papers based on the climatic zones and year of publication.

3.1. Key Findings

The reviewed studies span diverse topics, including empirical evaluations, optimization techniques, control strategies, and modeling approaches, as well as technical and economic assessments of demand response (DR). This collective body of work is instrumental in fostering innovative solutions targeting energy efficiency, reducing carbon emissions, and optimizing heating, cooling, and electricity systems within buildings. Importantly, these studies were conducted across a spectrum of building types, DR modeling approaches, DR management strategies, and research objectives.

Several studies have focused on empirical analyses of the demand response potential for commercial buildings. For instance, based on daily adjustments for cooling set points, the investigations have yielded significant reductions in cooling loads, resulting in potential savings of 13% to 28% for office buildings and 3% to 4% for laboratory buildings [44]. These findings underscore the tangible benefits of demand response in the commercial sector, paving the way for more efficient energy management practices. Furthermore, advanced techniques, such as deep reinforcement learning and planning guardrails, are giving promising results, outperforming traditional time-of-use pricing strategies and delivering substantial cost savings for building energy demand response [45]. These advancements highlight the potential of intelligent algorithms for optimizing energy consumption and curtailing energy costs.

With the focus on residential buildings, numerous studies have dedicated efforts to optimize space heating systems. Coordinated heating strategies, as proposed in [46], have showcased their capacity to trim system operational costs by nearly 14%, concurrently facilitating peak savings of about 28% while ensuring thermal comfort. These strategies leverage techniques like the economic model predictive control (E-MPC) to intelligently manipulate the heating demand, resulting in improved energy efficiency and decreased energy expenditures [46,55]. Additionally, dual-zone economic model predictive control schemes have demonstrated considerable promise in demand response for residential heating systems, leading to reduced energy consumption and costs when juxtaposed with baseline scenarios [47].

Research has addressed integrating renewable energy sources to enhance demand response and bolster the energy flexibility of buildings. Notably, photovoltaic systems [56,58,62] and ocean energy [67] have been the subject of investigation. These studies have unearthed the potential to satisfy a significant proportion of the electricity consumption of a building through on-site photovoltaic installations. They have also illuminated methods for optimizing the utilization of renewable energy through thermal storage capacity and precision control strategies aimed at maximizing the utilization of rooftop PV electrical energy, all while minimizing electricity expenses.

Furthermore, research endeavors have ventured into exploring the untapped potential of various building components and technologies, including PCM-enhanced building envelopes [63], hot water heat pumps [57], and energy storage systems [54,56,65,86]. These studies have yielded invaluable insight into the effectiveness of diverse strategies and their repercussions on energy consumption, cost mitigation, and peak load management. For example, Ref. [56] demonstrated the capability to offset up to 41% of electricity consumption in a building equipped with a PV installation. Additionally, the authors have unveiled the means to augment on-site PV electricity utilization using thermal storage capacity while devising control strategies for optimizing rooftop PV electrical energy usage, ultimately minimizing electricity costs. Furthermore, experimental validation of a model predictive control approach for demand-side management with a hot water heat pump has yielded notable results, including cost reductions (7–34%), energy savings (4–32%), and efficiency improvements (5–22%) in realistic settings [57].

For effective demand response and energy management, accurate forecasting of electricity demand emerges as a critical component. Machine learning models, including LSTM and SVM, are applicable in forecasting the electricity load within commercial buildings. These models take into account variables such as historical data, climate conditions, and occupancy patterns [51,60]. The outcome of these studies has underscored that LSTM-based models achieve higher prediction accuracy when a sufficient volume of data is available, while SVM-based models excel in scenarios with limited training data [60].

3.2. Distribution of Papers Based on Building Types and Sample Size

Based on the analysis of the selected research papers, most of the analyzed research papers (74%) focus on buildings within a specific sector: residential, commercial, or industry. Only 8% of the research papers analyzed buildings from both sectors (residential and commercial), and 6% covered all the sectors (residential, commercial, and industry). The remaining research papers did not provide explicit information on the specific type of building investigated.

The largest percentage (54%) of the analyzed papers examined less than 10 buildings. Notably, a significant proportion (78%) of these papers focused solely on one building. This factor suggests that a substantial number of studies performed an in-depth analysis of individual buildings rather than broader samples. The next most represented category was scientific papers that analyzed a large number of buildings (over 1000), accounting for 22% of the total analyzed sample. This indicates a considerable interest in investigating the implications and characteristics of large-scale building portfolios. Research papers analyzing a range of 100–1000 buildings constituted 12% of the analyzed sample, while a smaller portion (8%) of the analyzed sample focused on 10–100 buildings. These studies have likely struck a balance between analyzing individual buildings and broader trends observed on a larger scale (city or country). Figure 4 visually depicts the distribution of the analyzed research papers by size of the building sample investigated.

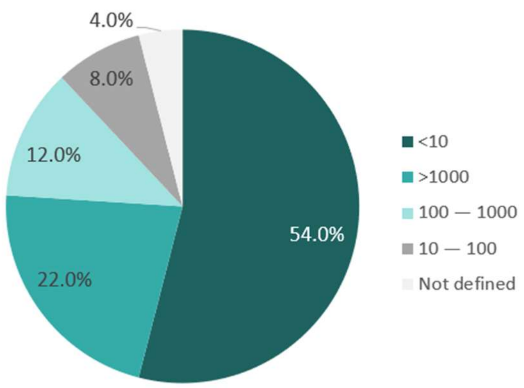


Figure 4. Distribution of analyzed papers based on the size of the building sample.

3.3. Distribution of Papers Based on DR Modeling Approaches

As previously mentioned, the estimation of demand response (DR) potential in buildings requires different modeling approaches, which are broadly categorized into three types: white box (physics-based), black box (data-driven), and gray box (combination of physics-based and data-driven). Most of the analyzed sample (92%) applied only one of the DR modeling approaches, while 8% of the research papers employed a combination of two DR modeling approaches. For instance, in [82], a hybrid approach was utilized by combining white-box and gray-box models. The authors employed a simulation model (white-box approach) to analyze the energy flexibility potential of buildings while also incorporating real-world weather conditions and building usage data (gray-box approach) to validate their findings. Overall, the analysis of the research papers demonstrates the prevalence of the gray-box approach, accounting for 50% of the sample; however, a notable portion of the sample also employed white-box (24%) and black-box (26%) modeling techniques, indicating the diverse methodologies used to estimate the DR potential in buildings. Figure 5 depicts the distribution of the analyzed research papers based on the DR modeling approaches used.

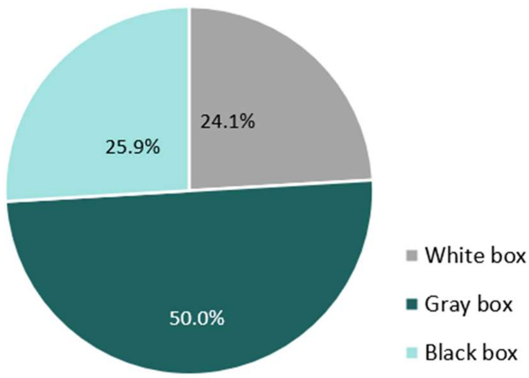


Figure 5. Distribution of analyzed papers based on the DR modeling approach.

An analysis of the dependency between an applied modeling approach and the size of a building sample gives noteworthy insights. The gray-box approach emerged as the most prevalent among the papers that analyzed less than ten buildings, accounting for 54% of the cases. In the case of research papers analyzing 10–100 buildings, the black-box approach had precedence, attributing to 80% of the studies. For research papers analyzing 100–1000 buildings and more than 1000 buildings, the gray-box approach was predominant, accounting for 57% of the cases in the 100–1000 building sample and 50% of the cases in the over 1000 building sample. Figure 6 provides a visual presentation of the various approaches employed in the analyzed papers based on the size of a building sample.

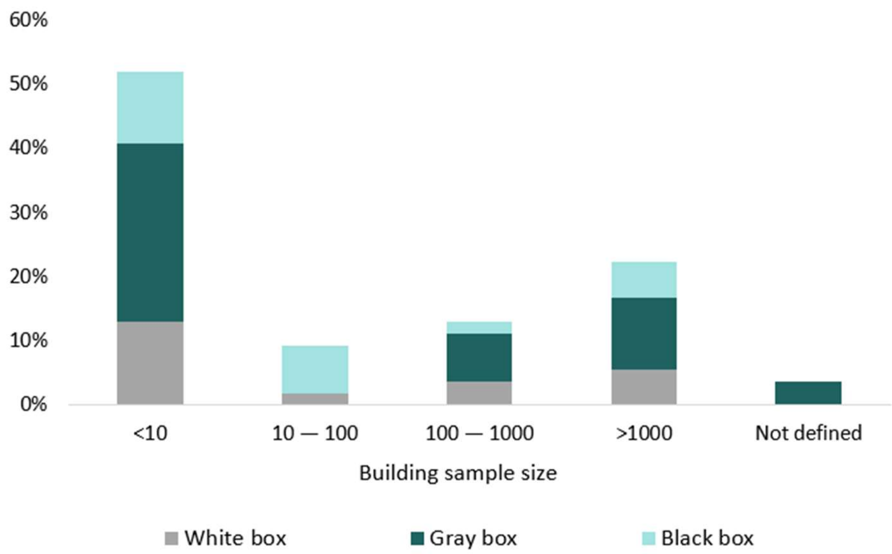


Figure 6. Relation between DR modeling approaches and building sample size.

The prominence of the gray-box approach in half of the analyzed papers suggests a preference for using it in demand response modeling. This fact is attributed to its unique ability to amalgamate the strengths of physics-based and data-driven methods. The gray-box approach provides an in-depth understanding of building systems while incorporating real-world data, making it a versatile choice.

The presence of the black-box approach in 26% of the papers indicates its effectiveness, albeit at a slightly lower prevalence than the gray-box method. Notably, this approach is favored in a substantial number of papers, particularly when dealing with datasets incorporating 10 to 100 buildings. The preference for black-box modeling in such cases is attributed to the ease of scalability, as it typically requires less detailed knowledge of the building's physical systems.

While the white-box approach is less common than the gray- and black-box approaches, its presence in 24% of the papers signifies its importance. White-box modeling is often chosen when a detailed understanding of a building's physical systems is necessary. This approach is particularly useful for smaller-scale building analyses, where detailed physical models provide valuable insight.

3.4. Distribution of Papers Based on DR Management Strategies

In Section 2.2, five primary DR management strategies were presented. These strategies covered efficiency, load shedding, load shifting, modulation, and generation. This section investigates the distribution of papers based on DR management strategies and the relation between the implemented DR management strategies and building sample size. However, it is worth noting that energy efficiency possesses the potential to achieve a permanent reduction in energy demand without necessitating significant changes in building operations. Furthermore, energy efficiency serves as a fundamental pillar for effective design; however, it alone is insufficient to meet the requirements of future buildings [1]. Consequently, this analysis will focus on exploring the remaining four types of strategies for demand-side management.

In the analyzed sample, 48% of the papers implemented only a single DR management strategy. Additionally, 32% of the papers employed two DR management strategies, while 10% utilized a combination of three strategies. Only 6% of the papers applied all the analyzed DR management strategies, including load shifting, load shedding, modulation, and generation. For 4% of the papers, the specific DR management strategy was not explicitly specified. Figure 7 shows the distribution of the analyzed research papers based on the number of DR management strategies used.

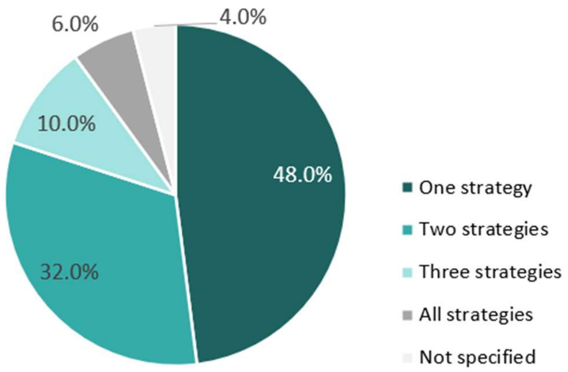


Figure 7. Distribution of analyzed papers based on the number of DR management strategies.

Figure 8 shows the dependency between DR management strategies and the size of a building sample. The research papers that analyzed less than ten buildings in most cases (56%) considered only one DR management strategy. Two DR management strategies were used in 26% of cases, while applying three or more strategies accounted for 15% of the cases. The remaining sample did not specify a specific DR management strategy. This pattern suggests that researchers often favor a singular strategy when confronted with smaller building samples. This preference may stem from the need to focus on a specific strategy, possibly due to limitations in data or resources, or to conduct an in-depth analysis of a single strategy. For research papers analyzing 10–100 buildings, a single DR management strategy was applied most often, constituting 50% of the cases. It suggests that researchers found the focused approach effective even when using moderately sized building samples. In research papers analyzing 100–1000 buildings, an equal representation of 33% was observed for the implementation of one and two DR management strategies. This equilibrium reflects the adaptability required to meet the diverse needs of moderately sized building samples. Research papers analyzing more than 1000 buildings implemented one DR management strategy in 36% of the sample. The percentage is significant, as it implies that even in extensive studies, a substantial portion of researchers prefer to focus on a single strategy. The utilization of two or more strategies was more prevalent, accounting for 55% of the cases. In summary, when analyzing the majority of building samples with less than ten buildings, the implementation of a single strategy prevails, suggesting that researchers possibly concentrate on a specific strategy. As the building sample size expands, the use of multiple DR management strategies becomes increasingly common, indicating a greater inclination among researchers to explore a broader spectrum of strategies when considering larger datasets.

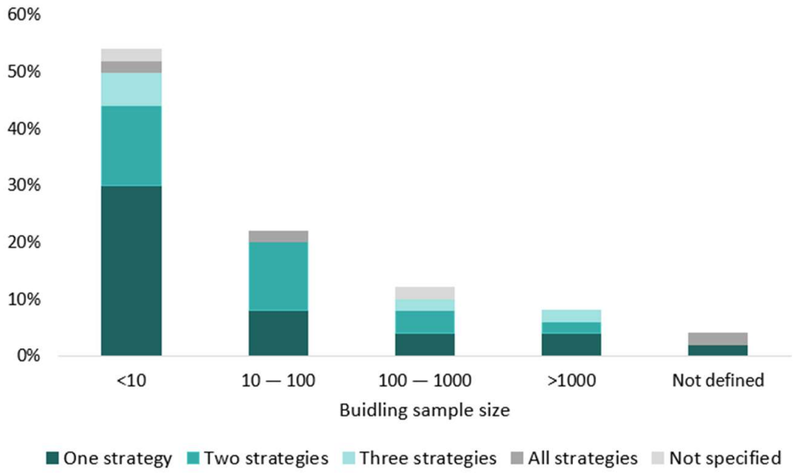


Figure 8. Relation between the number of DR management strategies and building sample size.

When considering the type of DR management strategy applied in the analyzed sample, the load shift strategy exhibited the greatest representation, accounting for 45%, followed by the load modulation strategy (27%) and the load shed strategy (20%). The energy generation strategy accounted for 6% of the sample. Figure 9 shows the distribution of papers based on employed DR management strategies.

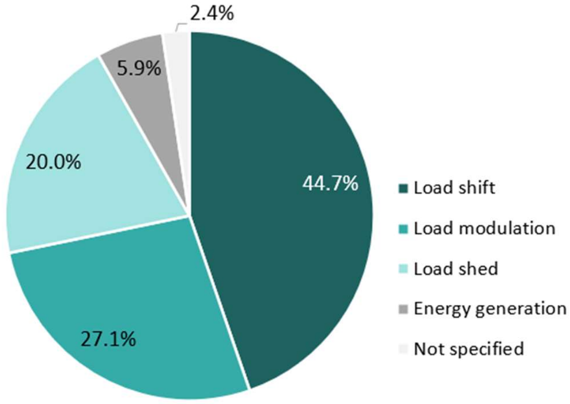


Figure 9. Distribution of analyzed papers based on the type of DR management strategy.

When considering the correlation between the type of DR management strategy and the size of the investigated building sample, a consistent pattern emerges across various building sample sizes. Regardless of the building sample size, the load-shifting strategy remained the most prevalent DR management strategy. These findings conform to a previous study [36] that ranked flexibility strategies by popularity: shift (60%), shed (19%), generation (16%), and modulation (5%). However, this analysis also shows a significant increase in the use of the load modulation strategy compared to the previous research [36]. The trend reflects the growing importance of dynamically adjusting energy consumption in specific building systems or equipment, which reflects the future of smart buildings. Figure 10 shows the analyzed research papers based on the type of applied DR strategy and building sample size.

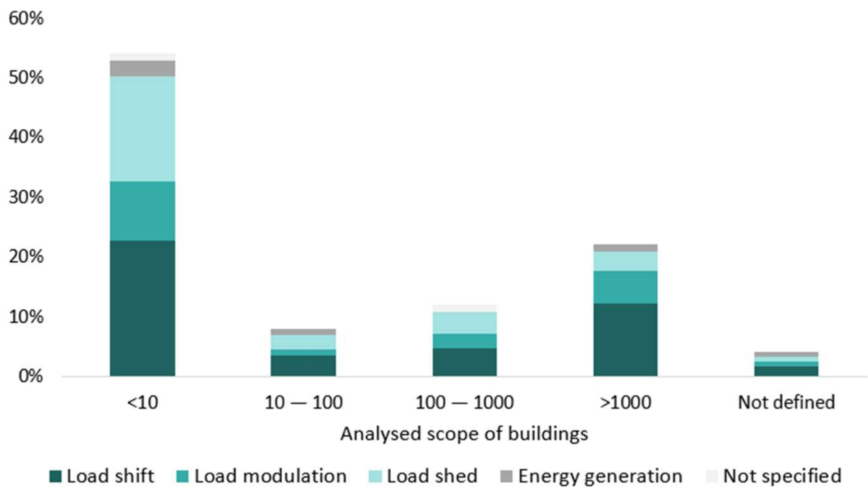


Figure 10. Relation between the type of DR management strategy and building sample size.

4. Discussion and Conclusions

This paper presents a statistical analysis of a carefully selected sample of the most recently published scientific research papers. The selected sample is crucial, as it ensures the inclusion of up-to-date research findings, thus enhancing the credibility and relevance of the study. The analyzed papers cover diverse research approaches, including the number and type of buildings, different optimization techniques, DR strategies, modeling approaches, and technical and economic assessments.

Notably, most of the analyzed papers (74%) focused on a specific type of building (residential, commercial, or industrial), showing a preference for a detailed investigation of individual buildings. This outcome suggests a particular research gap related to the comprehensiveness of analysis in this field. A wide-ranging approach targeting multiple building types and larger sample sizes would be highly beneficial because it provides a holistic understanding of demand response strategies for adaptability, enhances statistical reliability with diverse data, and encourages interdisciplinary collaboration on innovative solutions.

Concerning DR modeling approaches, the gray-box approach was the most prevalent, featuring in 50% of the analyzed papers, followed by the black-box approach in 26% and the white-box approach in 24% of the papers. The choice of the particular modeling approach often aligns with the scale of the studied buildings, with smaller-scale buildings more frequently being analyzed using the white-box and gray-box approaches. The substantial prevalence of the gray-box approach in approximately half of the analyzed papers signals a strong inclination towards its adoption in demand response modeling. This fact is attributed to its ability to combine the advantages of physics-based and data-driven methodologies. The gray-box approach provides a better understanding of building systems while seamlessly integrating real-world data, making it a versatile and favored choice.

Regarding DR management strategies, the load-shifting strategy was the most prevalent (45%), followed by load modulation (27%) and load shedding (20%). The energy generation strategy was relatively less represented. The findings suggest a consistent pattern across different building scopes, with load shifting widely implemented for demand response purposes. The findings correspond to previous research, confirming the popularity of certain types of flexibility. However, there is a notable increase in the load modulation strategy (from 5% in [36] to 27% in this paper), which aligns with the future vision of dynamically adjusting energy consumption in smart buildings.

The analysis also reveals that a significant portion of the sample applies a single DR management strategy (48%). However, there are merits in combining strategies, as is evident by the utilization of two or three management strategies in a portion of the sample. This trend not only reflects past approaches but also foreshadows the future, offering a glimpse into the ever-evolving landscape of building management. In the coming years, as buildings continue to evolve in complexity, and their energy demands become increasingly intricate, the versatility shown in the simultaneous use of multiple DR management strategies will only grow in importance. This adaptability will be vital as modern structures seek to meet the multifaceted challenges of sustainability, efficiency, and dynamic energy management.

In conclusion, this research provides significant academic and technological contributions to the field of demand response (DR) in buildings. The predominant focus on specific building types within the analyzed papers underscores an existing research gap in the comprehensive analysis within this field. Addressing this gap is crucial, as future studies should adopt a more encompassing approach that includes multiple building types and larger sample sizes. Such an approach ensures a holistic understanding of demand response strategies, enhances statistical reliability through diverse data integration, and fosters interdisciplinary collaboration for innovative solutions. In terms of social insights, the evolving landscape of demand response emphasizes the importance of adaptable approaches to building management, particularly in the realms of sustainability, efficiency, and dynamic energy use. Furthermore, this research provides practical implications. It contributes to understanding the current practices in DR research for buildings and provides valuable insights into the factors influencing the choice of building sample sizes, DR modeling approaches, and DR management strategies. These findings are a valuable resource for future studies and decision-making processes related to the potential assessment of DR in buildings. However, what is evident is that trends are changing. In terms of future research, it would be beneficial to statistically track the ongoing development of the situation and establish a correlation with the geographical location, as the progress of countries undoubtedly influences the implementation of DR. Accordingly, examining variables such as technical readiness, economic readiness, legal preparedness, and social barriers provides a more comprehensive understanding of the factors influencing the implementation of DR in a particular country.

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